The influence of dark pool activity on the open market price impact of takeover rumors

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Abstract

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Using takeover rumors as informed trading events, this paper investigates dark pool trading characteristics as well as the influence of dark pool activity on the price impact in open markets. We find that dark pool participation impacts return, volatility and bid–ask spread of the rumored takeover targets. A closer examination of the trading venues reveals that as the relative trading volume in dark pools increases, the price discovery in the dark pool also sees a marginal increase. Interestingly, most of the permanent price impact seems to emanate from small size trades. A possible explanation could be that because of the low execution probability in dark pools, informed traders prefer to slice their orders into small pieces.

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1. Introduction

Alternative trading systems (ATSs) flourished after the U.S. Securities and Exchange Commission (SEC) accepted the Regulation National Market System in 2005. In 2015, around 18 percent of total dollar volume of the market was traded on ATS.[1] According to the SEC, dark pools are a type of alternative trading system (ATS) that does not provide order information to the public.

Dark pools were initially designed for investors to trade large blocks of shares without facing the adverse price pressure created by their trade. To protect market stability, dark pools enable anonymous trading. Anonymity prevents a large trade from drawing too much attention, and thus avoids significant price impact. However, on the flip side, the same anonymity also has the potential to hide information and thereby adversely affect price discovery. Furthermore, this adverse effect may not remain contained to the dark pool. It can harm the price discovery process of the open market by absorbing too many trades and liquidity from non-dark pool venues. Buti, Rindi and Werner (2011) show that when dark pools are introduced, traders reduce the size of their orders in the Limit Order Book and switch to dark pools. They found that even though the combined total volume in the Limit Order Book and the dark pool increased, the increase was largely driven by the increased trading on the dark pool venue. Consistent with this, Nimalendran and Ray (2013) suggest that trades in dark pools provide less information to the open market and therefore, potentially informed traders are likely to break their orders across dark pools and open markets. Ye (2011) finds that dark pools hurt price discovery and increase volatility and that the execution probability and competitiveness of dark pools are reduced by informed trading. However, some other more recent studies make contradictory assertions. Zhu (2014) points out that dark pools improve price discovery in the open market. Zhu (2014) argues that informed orders are positively correlated with each other and therefore, informed traders are likely to trade in the same direction as the market. To the extent that this is likely to lower the execution probability, it is likely to push informed traders into the open market. As more informed investors trade in open markets, the noise on the exchange reduces and the price discovery ability of the open market improves.

[1] Regulation Systems Compliance and Integrity, Securities Exchange Act Release No. 73639, p.55 (Nov. 19, 2014) (noting that "based on data collected from ATSs pursuant to FINRA Rule 4552 for 18 weeks of trading in 2014, the trading volume of ATSs accounted for approximately 18 percent of the total dollar volume in NMS stocks, with no individual ATS executing more than five percent").

This paper uses M&A rumors as an exogenous information event to examine the influence of dark pool trading on price impact in open markets. We investigate whether the relative trading volume in dark pools adversely impact the price discovery process in the open market. To answer this question, we perform several event studies. Instead of using acquisition announcements, we use takeover rumors as the events. Compared to acquisition announcements, which typically lead to abnormal returns and high volatility before the announcement due to information leakage, rumors are more unexpected and hence, should give us a better picture of the impact of dark pools. Ahern and Sosyura (2015) examine takeover rumors from January 1, 2000 to December 31, 2011 and show that the target firm experiences a 4.3% abnormal stock return on the publication day of the initial takeover rumor. Chou, Tian and Yin (2010) show the price of takeover rumor targets moves 42 days before the takeover rumor occurs. In contrast, for acquisition announcements, Huang and Walking (1987) show the takeover target firm gains a 9.3% abnormal return on the initial acquisition announcement day. Betton and Eckbo (2000) find the price of acquisition targets starts to move upward 60 days prior to the takeover announcement. Many previous studies find pre-bid run-up in the price of takeover target stocks. Comment and Jarrell (1987) find that from 1984 to 1989, shareholders received a 50 percent return on the price of stocks that were traded before tender offers. Jarrell and Poulsen (1989) study how markets anticipate tender offers and find that pre-bid run-up anticipates around 40 percent of takeover premiums.

We attempt to link open market performance with relative trading volume in dark pools. Four aspects of a stock—return, abnormal return, volatility and bid–ask spread—are used to measure market performance in light of rumors. We want to know whether the relative dark pool trading volume of a stock associated with an acquisition rumor significantly impacts these four aspects on the event date. Our methodology closely follows Barclay and Warner (1993). We classify the transactions in dark pools and open markets into several categories based on trading size. Our results are consistent with the findings of Barclay, Hendershott and McCormick (2003) that informed traders in dark pools prefer small trades. With the rapid development of algorithmic trading, block traders and informed traders can reduce their transaction costs by slicing large orders into smaller ones over time. Hendershott and Jones (2011) suggest that institutions would use algorithmic trading to gradually accumulate or dispose shares. Hendershott and Riordan (2013) find that institutional investors trade large block shares in small lots gradually over time, and minimize the transaction cost with the help of algorithms. Further investigation finds that the dark pool price discovery does not seem to be related either to the accuracy of the rumor, or, to the fundamentals of the firm. In contrast to the dark pool results, we find that the price discovery process in the open market does depend on both the accuracy of the rumor and the fundamental characteristics of the firm. To the extent that there are no market makers in the dark pool, a possible interpretation of these results may be that informed investors in dark pools do not react similarly to information because of the poor liquidity. We also find some evidence suggesting that the percentage of price discovery in dark pools increases along with growth in the relative trading volume in dark pools. This means that greater price discovery emanates from dark pools as the relative trading volume in dark pools increases.

The remainder of the paper is arranged as follows. In Section 2, we review the previous studies related to dark pools and rumors. In Section 3, we describe the data used in the paper. In Section 4, we analyze the effect of dark pools on open market performance. In Section 5, we provide the trading distribution of both venues under various criteria. We conclude in Section 6.

2. Literature review

2.1 Dark pools

Many existing theories investigate the characteristic of dark pools and how they influence overall market quality. Bloomfield and O'Hara (1999) find that prices concentrate more quickly in transparent markets and that the level of market transparency has a crucial influence on market equilibria, benefitting traders and market makers. Bloomfield, O'Hara and Saar (2015) suggest that the transparency of trading venue impacts the benefits for informed traders. Boni, Brown and Leach (2012) show that large trades in dark pools are insignificantly correlated with returns and drive a lower volatility increase. Comparing dark pools to open markets, Buti, Rindi and Werner (2011) suggest that when dark pools are introduced, traders favor them to the Limit Order Book; thus, the volume in the Limit Order Book always decreases, even when the total volume of both the Limit Order Book and dark pools is raised. Conrad, Johnson and Wahal (2003) provides evidence suggesting that alternative trading systems have lower realized execution costs than systems relying on brokers. Finally, Degryse, Jong and Kervel (2014) suggest that market liquidity is enhanced by the competition of lit and dark venues.

Extant studies remain contradictory on whether dark pools hurt price discovery in open markets. Ye (2011) finds that the existence of dark pools reduces price discovery ability of open markets. Klöck, Schied and Sun (2011) analyzed dark pool regularity and find that dark pools may lead to market inefficiencies and decreased value-finding. On the other hand, Zhu (2014) points out that even when the liquidity of exchanges is damaged by the existence of dark pools, price discovery improves. Buti, Rindi, Wen and Werner (2011) examine stock depth, spreads and short-term volatility and show that high dark pool participation improves market quality. Furthermore, Mizuta et al. (2015) indicate that dark pools can prevent large market impact and stabilized prices.

2.2 Takeover rumors

Extensive prior literature explains the positive abnormal return on targets of takeover rumors. Pound and Zeckhauser (1990) find that markets react to takeover rumor information efficiently, while Keown and Pinkerton (1981) prove that pre-announcement trading is based on takeover rumors and that inside information always leaks before the announcement. Chou, Tian and Yin (2010) find that the stock price run-up before a rumor's publication predicts the accuracy of the rumor, and Ahern and Sosyura (2015) show that rumors from journalists who have superior experience or specialization in the corresponding industry strongly predict the takeover announcement. Betton, Davis, and Walker (2017) find that the justification behind the takeover rumor is significantly correlated with rumor accuracy as well as short and long-run abnormal returns. Engelberg, Joseph and Parsons (2011) show that the existence and timing of local media reporting greatly affect local trading. Similarly, Liu, Smith and Syed (1990), after studying the "Heard on the Street" section of *The Wall Street Journal*, report positive abnormal returns 10 days prior to the date information becomes public. Pound and Zeckhauser (1990) and Zivney, Bertin and Torabzadeh (1996) also investigate takeover rumors in *The Wall Street Journal* and find that, on average, takeover rumor target firms experience approximately seven percent excess returns during the twenty trading day period before the rumor is published. Clarksona, Joyceb and Tutticcia (2006) analyze intraday data and find high trading volume and high abnormal returns on a stock in the 10-minutes time interval immediately after the takeover rumor is posted on the Internet. Furthermore, Bommel (2003) suggest that when rumors occur, the stock price moves and informed traders rebalance their portfolios.

3. Data collection

3.1 The takeover rumor data

We use the rumor data of Betton, Davis, and Walker (2017) and subsequently define a rumor as any publicly available conjecture that explicitly claims that a public U.S. firm recorded in the Centre for Research in Security Price (CRSP) database is a potential acquisition target. To guarantee public awareness of the conjecture, the information also has to be reported in business journals, publications or the media. Therefore, rumor data was collected from S&P Takeover Talk, S&P Capital IQ, Zephyr, plus two online databases, Factiva and Pro-Quest, which collect reports from various leading publications, including *The Wall Street Journal*, *Business Week*, *The Economist*, *Bloomberg* and *Dow Jones Newswires*. Rumors were collected using a proprietary algorithm containing the keywords "strategic alternative", "buyout", "sale of the firm", "looking to be acquired", "takeover candidate", "takeover chatter" and other sets of takeover terms to identify rumors.

Furthermore, the rumors collected represent the initial ('scoop') publication, ensuring no similar public conjectures within the previous 180 days. If a rumor does not occur on a trading day, we adjust the event date to the next trading day. Of their complete sample of 2074 takeover rumors, we identify 1,279 rumors announced between January 1, 2006 and December 31, 2010 which comprise the full sample for this study since dark pool trading has truly flourished after 2005.

3.2 The dark pool trading data

We collect the dark pool intraday trading data from the Trades and Quotes (TAQ) database, which gives us transactions across dark pools and exchanges. The dark pool trading sample includes the stocks recorded in the CRSP database from January 3, 2006 to December 31, 2010.

To distinguish dark pool trades from transactions settled in exchanges, we use the TAQ exchange code to classify trades in dark pools, as represented by the letter "D" in the TAQ database.

4. The performance of open markets under different levels of dark pool participation

To uncover how dark pools impact market performance, we design a set of variables to capture the relative performance of the two markets (dark pool versus the open market). We select four variables—return, abnormal return, volatility and bid–ask spread—to report the performance of the market. Return and abnormal return measure the reaction of the market to takeover rumors. Previous studies indicate that rumors drive significant abnormal returns for acquisition targets. We examine the return and the abnormal return in the open market and contrast it with that in the dark pool to understand the price discovery in the two venues. Volatility measures the fluctuation and range of prices. We are investigating the prices around an information event (M&A rumors). Arrival of new information in the market and the price discovery process that follows it is likely to increase the volatility in the market. Therefore, we expect stock prices to become more volatile and the stock's price range to widen in the face of rumors. Close examination of the volatility of prices on the open market and the dark pool allows us to develop a better understanding of the price discovery process and the role of the dark pool. We also use the bid–ask spread to measure market liquidity and information asymmetry. Arrival of new information in the market should lead to widening of the bid-ask spread. As the price discovery process evolves, the spread should gravitate towards its pre-information levels. If dark pools are adversely affecting the price discovery process, then we would expect that the bid-ask spreads would take longer to return to their pre-event levels.

A crucial variable of interest in this paper is dark pool participation. To remove the size effect of different stocks, we capture dark pool participation by calculating the relative trading volume in dark pools. Following Tkac (1996) and Lo and Wang (2000), we define relative trading volume in dark pools as:

$$RV_{i,t} = VDP_{i,t}/(VOM_{i,t} + VDP_{i,t})$$

Where $RV_{i,t}$ is the relative trading volume in dark pools, $VDP_{i,t}$ is the daily dollar trading volume in dark pools and $VOM_{i,t}$ is the daily dollar trading volume in open markets for stock *i* on event date *t*.

Return is the daily return of the stock on the event date. Abnormal returns are calculated by subtracting the estimated return, measured by the market model, from the actual return on the event date. The event date is the rumor date or the closest trading day after the rumor date, if the rumor day is not a trading day. To avoid material event impact, we would like to choose an estimate window containing minimal important public information. As the takeover rumor data already selected the rumor without public conjecture within the previous 180 days, daily returns for 50 trading days, which cover the period *t-100* though *t-50*, are used to estimate the market model parameters, where day *t* represents the event date for the security. The abnormal return of a security on day *t* is calculated as the difference between the actual return and the estimated return of the market model as follows:

$$AR_{i,t} = R_{i,t} - RE_{i,t}$$

Where $AR_{i,t}$ is the abnormal return, $R_{i,t}$ is the exact return and $RE_{i,t}$ is the estimated return, as calculated by the market model for stock *i* on event date *t*.

We measure daily volatility by calculating the natural logarithm of the price range on the event date. Rather than compute the dispersion of the price, this measurement provides the scope of price movement on the event date. Following Parkinson (1980), the trading volatility of a stock on the event date is defined as:

$$\sigma_{i,t} = \ln(\frac{P_{H,i,t}}{P_{L,i,t}})$$

Where $\sigma_{i,t}$ is trading volatility, $P_{H,i,t}$ is the highest trading price and $P_{L,i,t}$ is the lowest trading price for stock *i* on event date *t*.

To the extent that the quoted bid-ask spread is a function of the stock price, we use relative bid spread (RS) in this study. In order to avoid issues of bid-ask bounce, we use quote mid-point instead of the transaction price. Therefore, daily relative bid–ask spread is defined as the bid–ask spread at market close divided by the quote mid-point (mid-quote MQ):

$$RS_{i,t} = \frac{Spread_{i,t}}{MQ_{i,t}}$$

Where $RS_{i,t}$ is the relative bid–ask spread, $Spread_{i,t}$ is the bid–ask spread at market close and $MQ_{i,t}$ is the quote mid-point at market close for stock *i* on event date *t*.

Summary statistics of the variables are presented in Table 1. The *t* statistics indicate that return, abnormal return, volatility and bid–ask spread are all significantly different from zero. This result is consistent with the findings of Gupta and Misra (1988), Jarrell and Poulsen (1989), Clarkson, Joyce and Tutticci (2006), Betton, Eckbo and Thorburn (2008), Jain and Sunderman (2014), and Betton, Davis, and Walker (2017) that takeover rumors have substantial impact on stock price.

To explore the impact of dark pools, we run several linear regressions that treat the relative volume in dark pools as the independent variable. Cornett et al. (2011) investigated both firm and industry level variables, which are used to predict takeover candidacy. By incorporating the control variables mentioned in Cornett et al. (2011), and the dummy variable *takeover announced within six months,* which indicates whether the takeover rumor comes true within six months, we control for firm and industry fundamentals and rumor accuracy which are factors that may impact market performance. Following Cornett et al. (2011), we use the following model to explore the impact of dark pools on the trading environment in the market:

$$PIP = \alpha + \beta_1 * RV + \beta_2 * (sales\ \ shock) + \beta_3 * (sales\ \ shock\ \ squared) + \beta_4 * (size) + \beta_5 * (change\ \ in\ \ size) + \beta_6 * (sales\ \ growth) + \beta_7 * (concentration\ \ ratio) + \beta_8 * (resource\ \ growth\ \ mismatch) + \beta_9 * (ROA) + \beta_{10} * (share\ \ turnover) + \beta_{11} * (cash\ \ ratio) + \beta_{12} * (previous\ \ bids) + \beta_{13} * (dormant\ \ period) + \beta_{14} * (price\ \ runup) + \beta_{15} * (information\ \ asymmetry) + \beta_{16} * (takeover\ \ announed\ \ within\ \ six\ \ months) + \varepsilon$$

Where PIP is price impact proxies which are return, abnormal return, volatility and bid-ask spread, RV is the relative trading volume in dark pools, $sales\ \ shock$ is the absolute value of the difference between the two-year median industry sales growth and the two-year median sales growth for all firms in the sample, $sales\ \ shock\ \ squared$ is square of sales shock, $size$ is the log of total assets, $change\ \ in\ \ size$ is the percentage change in the book value of assets of the firm in the last two years, $sales\ \ growth$ is the change in the firm's net sales in the last two years, $concentration\ \ ratio$ is the ratio of sales of the largest four firms (in terms of sales) to total industry sales, $resource\ \ growth\ \ mismatch$ is a dummy variable equal to one if i) sales growth for a firm in the last two years is less than the industry median and long-term debt ratio is greater than the industry median, or ii) if sales growth in the last two years is greater than the industry median and long-term debt ratio is less than the industry median, and zero otherwise, ROA is the ratio of net income before extraordinary (or nonrecurring) items to total assets, $share\ \ turnover$ is the ratio of the number of shares of stock traded for the firm to the total shares outstanding, $cash\ \ ratio$ is the ratio of cash to total assets. $previous\ \ bids$ counts the number of times a firm proposes or receives a merger bid in the prior two years, $dormant\ \ period$ is the number of months since the last merger in the industry (industry is defined at the 3-digit SIC level), $price\ runup$ is the percentage change in a firm's stock price in the prior two years, $information\ \ asymmetry$ is a dummy variable equal to one if the market-to-book ratio is higher than the industry median and share turnover is lower than to the industry median and zero otherwise, $takeover\ \ announed\ \ within\ \ six\ \ months$ is a dummy variable equal to one if the rumor target involved in an actual acquisition in six months. Appendix A gives the description of all control variables used in these regressions.

The results of the regressions are presented in Table 2, where model 1 shows the results of the regression that includes only the control variables and model 2 gives the results of the full regressions. The adjusted R-squared of these four regressions all increase when adding the variable *relative volume in dark pools*, which is positively significant in all of the full regressions. These results indicate that when experiencing high levels of dark pool participation, a stock's return, abnormal return, volatility and bid–ask spread increase accordingly. A stock with high dark pool participation tends to enlarge both the stock return and abnormal return when a takeover rumor is first published. That stock volatility and bid–ask spread rise along with relative volume in dark pools reveals that price discovery in open markets is harmed by a high level of participation in dark pools. Basically, markets search for the right price within a wide range, and investors are unwilling to buy (or sell) a stock at a higher (or lower) price because of a lack of market liquidity when they do not know the appropriate stock price. Therefore, adding dark pools alongside open markets influences price discovery in open markets.

The significance of the variable *takeover announced within six months* agrees with the findings in previous studies that rumor accuracy impacts the open market stock performance on the event date. However, when testing the correlation between the relative volume in dark pools and the variable *takeover announced within six months*, we find the correlation coefficient to be -0.025. Contrasting this negative coefficient with the positive correlation observed between the relative volume in open markets and the variable *Takeover announced within six months* seems to suggest that the association between rumor credibility and informed trading seems to differ across the trading venues.

When we consider that investors in open markets have strong reactions to accurate rumors, despite possessing knowledge inferior to informed dark pool traders, it seems unlikely that this difference is caused by the incautiousness of dark pool investors. With the absence of market makers, orders in dark pools are far more difficult to execute than those in open markets; thus, informed traders are not always able to transact as many shares as they want. Therefore, informed traders in dark pools may be unable to react strongly to accurate rumors, even if they would like to. We examine this explanation further in the following part of this paper.

5. Price movement in both dark pools and open markets under different levels of dark pool participation

We further examine the cumulative price change of a stock in dark pools and open markets on the event date following the methodology used in Barclay and Warner (1993). Barclay and Warner (1993) study the typical trading size of informed traders and find that maximum price discovery takes place in trades of 500 to 10,000 shares. They define the percentage of the cumulative price change for a given firm as the sum of all stock price changes occurring on trades in a given size category divided by the total cumulative price change over the event period. We follow this definition and examine price discovery primarily according to trading venue rather than trading size.

Table 3 gives the trading distributions in both dark pools and open markets and the corresponding percentage of cumulative price change in different trading size categories. When calculating the mean percentage of total share volume and the mean percentage of cumulative price change, we eliminate the size effect of different stocks be giving these two values equally weighted averages.

We find that despite relative trading volume being lower in the small trading size category than the medium trading size category in dark pools, most cumulative price change occurs in small trades, mainly of 100 shares. This indicates that small trades have the largest effect on prices in dark pools. This result is quite different from the findings of Barclay and Warner (1993) but consistent with those of Zhu (2014) and Barclay, Hendershott and McCormick (2003). The difference in price impact across order sizes might be caused by diverse trading motivations of investors in different size categories. Since Armstrong, Core, Taylor and Verrecchia (2011) indicate that informed traders have a greater impact on price due to superior information, we believe stock price is mainly moved by informed traders. This may manifest itself more in small trades as Caskey, Hughes and Liu (2015) show that informed traders tend to hide their positions by splitting large orders into small slices. The development of algorithmic trading further strengthens the preference for small trades. The majority of algorithmic strategies and trades focus on reducing transaction costs (Hendershott and Jones, 2011; Hendershott and Riordan, 2013; Shen, 2013; Shen and Yu, 2014). To reduce these costs, a large order is sliced into small pieces and offered progressively. Institutional traders, in particular, prefer algorithmic trading because it allows them to minimize transaction costs.

We also find the majority of price change still occurs in open markets. This finding confirms the results of previous studies that compared to orders on exchanges, off-exchange orders contain less information (Jiang, McInish and Upson, 2011; Zhu, 2014; Degryse, Jong and Kervel, 2014; Comerton-Forde and Putniņš, 2015). Zhu (2014) finds that informed traders like to trade in the same direction as the market, which lowers execution probability in dark pools. By contrast, liquidity orders are uncorrelated with each other and trade on different sides of the market; thus, in dark pools, liquidity orders tend to have higher execution probabilities than informed orders. Because execution in open markets is assured by market makers, the percentage of trading volume for small trades in dark pools is lower than that percentage in open markets.

Table 4 and Table 5 use firm size and return on assets (ROA) as the quantile study criteria and find that cumulative price changes are non-proportional to trading volume, which holds for different firm sizes and ROA categories. The percentage of total share volume and the percentage of total cumulative price change for different firm sizes and ROA quantiles are similar. Therefore, firm size and ROA have no impact on investor behavior in dark pools; informed traders use the same strategy to maximize their benefits and unable to react to the fundamentals of the company.

We then examine dark pool performance in light of both accurate and inaccurate rumors. A rumor leading to a real takeover announcement within the next six months is considered an accurate rumor at six months and a rumor leading to a real takeover announcement within one year is considered an accurate rumor at one year. Table 6 gives the market conditions for both accurate and inaccurate rumors. The differences in the percentage of total share volume and total cumulative price change under these four situations are not significant, consistent with our hypothesis that because of the liquidity conditions in dark pools, informed traders in dark pools cannot suitably react to rumors whether accurate or inaccurate.

To test whether dark pool participation levels influence the percentage of cumulative price change in both lit and dark venues, we divide the observations into four groups, based on the quantile of relative trading volume in dark pools, and examine the trading distributions. Table 7 presents the percentage of cumulative price change under different quantiles of the relative trading volume in dark pools and the open market.

The percentage of cumulative price change in dark pools rises along with the growth of trading volume in dark pools. As the relative trading volume in dark pools increases, greater price discovery emanates from the dark pool. This price discovery mainly comes from small trades. This result reinforces our opinion that adding dark pools influences the price impact in open markets.

We present the repeat tests across the time horizon in Table 8 and Figure 1 and find that the trading volume in dark pools rose between 2006 and 2010. Generally speaking, the percentage of total share volume and total cumulative price change in dark pools increased during this period and stabilized after 2008. This trend suggests that dark pools have become more attractive to investors. We also find the total share volume in dark pools in 2007 increased while the cumulative price change decreased compared to 2006. To further explore this unusual decrease, instead of using the equal weighted average, we consider the size effect and utilize the value-weighted average of trading volume in both dark pools and the open market. Table 9 and Figure 2 present the results using the value-weighted average. In 2007, the percentage of the value-weighted trading volume of small trades in dark pools decreased, which means that investors, especially institutional investors, tended to make transactions in open markets in that year. This unusual decrease might have been caused by the financial crisis of 2007–2008. Because there are no market makers in dark pools, orders in dark pools might not get executed. This execution probability is decreased further when considering that informed traders in dark pools generally like to trade in the same direction under material information. In a financial crisis, this trading preference of informed traders increases and pushes them to settle their orders on open markets. Therefore, the equal weighted average cumulative price change in dark pools in 2007 was relatively lower.

6. Conclusion

In this paper, we look at the influence of dark pool activity on price impact in open markets and at dark pool trading characteristics in light of rumors. Rumors are used as events because they are considered unexpected material information. We find that the relative trading volume in dark pools is strongly and positively correlated with daily return, abnormal return, volatility and the bid–ask spread of a stock on the event date. This result indicates that dark pool participation significantly impacts the performance of open markets. Furthermore, we find dark pool participation is negatively correlated with rumor accuracy. Given dark pools have low market liquidity and the performance of the open market under various takeover rumor and company fundamental conditions differs greatly. we conclude that investors in dark pools are unable to appropriately respond to credible information. Increased dark pool participation also drives high stock volatility and bid–ask spread, which means that markets search for the right price within a wider range and investors are unwilling to buy (or sell) the stock at a higher (or lower) price because of a lack of market liquidity, given their imperfect knowledge of the appropriate stock price.

Evidence from trading volume and cumulative price change in different trading size categories in dark pools reveals that even though the trading volume of small trades is lower than or close to that of medium trades, most cumulative price change occurs on small trades. This suggests that because of the low execution probability of dark pools, informed traders prefer to slice their orders into small pieces in light of takeover rumors. This phenomenon also holds in multiple situations. The quantile study results indicate that the price impacts of dark pools on the open market remain similar, despite differences in rumor accuracy, firm size and firm ROA conditions. This confirms our previous finding that investors in dark pools are restricted from reacting to rumor information. Overall, the undifferentiated price impact of dark pools on open markets under multiple situations indicates that although informed traders are likely to fully utilize their private information and set their positions in every trading venue, dark pools cannot execute orders in a short period of time because they lack market makers.

We also find that the percentage of cumulative price change in dark pools rises along with the growth of trading volume in dark pools. As the relative trading volume in dark pools increases, greater price discovery emanates from dark pools. In this case, dark pools absorb market liquidity, and the participation level of dark pools influences the price impact on open markets.

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Appendix A

The definition of the control variables used in the empirical analyses. These definitions, except "Takeover announced within six months", replicate the definitions in Cornett et al. (2011)

Variable	Definition
Sales shock	The absolute value of the difference between the two-year median industry sales growth and the two-year median sales growth for all firms in the sample
Sales shock squared	Square of sales shock
Size	The log of total assets
Change in size	The percentage change in the book value of assets of the firm in the last two years.
Sales growth	The change in the firm's net sales in the last two years.
Concentration ratio	The ratio of sales of the largest four firms (in terms of sales) to total industry sales.
Resource-growth-mismatch	A dummy variable equal to one if i) sales growth for a firm in the last two years is less than the industry median and long-term debt ratio is greater than the industry median, or ii) if sales growth in the last two years is greater than the industry median and long-term debt ratio is less than the industry median, and zero otherwise.
Return on assets (ROA)	The ratio of net income before extraordinary (or nonrecurring) items to total assets.
Share turnover	Ratio of the number of shares of stock traded for the firm to the total shares outstanding.
Cash ratio	Ratio of cash to total assets.
Previous mergers	Counts the number of times a firm proposes or receives a merger bid in the prior two years.
Dormant period	The number of months since the last merger in the industry (industry is defined at the 3-digit SIC level).
Price run-up	Percentage change in a firm's stock price in the prior two years.
Information asymmetry	Dummy variable equal to one if the market-to-book ratio is higher than the industry median and share turnover is lower than to the industry median and zero otherwise.
Takeover announced within six months	Dummy variable equal to one if the rumor target involved in an actual acquisition in six month and zero otherwise.

Appendix B

Table1
Summary statistics on market performance variables on the event date.
For each individual stock, Return is calculated by the close to close stock return; abnormal return is measured by a market model; volatility is Parkinson range volatility; bid-ask spread is the bid – ask quote at the market close; and relative trading volume in dark pool is the proportion of total trading volume in the market conducted in dark pools. This table presents the moments of these variables.

Moments	**Return**	**AR**	**Volatility**	**Spread**	**Relative Volume**
N	1238	1238	1238	1238	1238
Mean	0.042	0.040	0.032	0.004	0.277
Std. Deviation	0.114	0.112	0.034	0.016	0.143
Variance	0.013	0.013	0.001	2×10^{-4}	0.021
Skewness	11.761	11.913	4.393	13.195	0.350
Kurtosis	268.710	271.799	32.499	245.552	0.771
75% Q3	0.0639	0.059	0.039	0.002	0.360
Median	0.023	0.019	0.023	9.8×10^{-4}	0.275
25% Q1	0	-7×10^{-4}	0.014	4.7×10^{-4}	0.191
t value	13.066	12.492	34.038	8.913	67.952
Pr > |t|	<.0001	<.0001	<.0001	<.0001	<.0001

Table 2
OLS regressions of return, abnormal return, volatility and bid-ask spread. Model 1 provides the result of the regressions only include control variables. Model 2 gives the result of the regressions adding the variable *relative trading volume in dark pool* on Model 1.
*To facilitate understanding, coefficients are multiplied by 100.

	Return		**AR**	
	Model 1	Model 2	Model 1	Model 2
Intercept	-0.02 (0.998)	-1.77 (0.744)	1.76 (0.742)	0.07 (0.989)
RV	-	8.71** (0.001)	-	8.38** (0.002)
Sales shock	14.64* (0.021)	14.13* (0.026)	14.40* (0.022)	13.90* (0.026)
Sales shock squared	-17.84 (0.060)	-16.95 (0.073)	-17.06 (0.069)	-16.20 (0.083)
Size	-0.51* (0.038)	-0.32 (0.210)	-0.41 (0.093)	-0.22 (0.373)
Change in size	-0.83 (0.050)	-0.78 (0.067)	-0.81 (0.053)	-0.76 (0.070)
Sales growth	0.08 (0.252)	0.08 (0.262)	0.07 (0.282)	0.07 (0.293)
Concentration ratio	0.27 (0.888)	0.33 (0.861)	0.01 (0.996)	0.07 (0.970)
Resource-growth-mismatch	0.31 (0.663)	0.26 (0.715)	0.29 (0.677)	0.24 (0.729)
Return on assets (ROA)	7.20 (0.082)	8.74* (0.036)	5.78 (0.158)	7.25 (0.077)
Share turnover	0.48 (0.220)	0.32 (0.414)	0.28 (0.476)	0.12 (0.753)
Cash ratio	-1.46 (0.465)	-1.38 (0.489)	-0.95 (0.632)	-0.86 (0.660)
Previous mergers	-0.12 (0.593)	-0.15 (0.509)	-0.16 (0.488)	-0.19 (0.415)
Dormant period	-0.02 (0.700)	0.00 (0.944)	-0.01 (0.775)	0.00 (0.980)
Information asymmetry	0.54 (0.751)	0.62 (0.715)	0.16 (0.923)	0.24 (0.887)
Takeover announced within six months	5.83*** (<.0001)	5.93*** (<.0001)	6.12*** (<.0.001)	6.21*** (<.0001)
N	1053	1053	1053	1053
R-squared	0.04298	0.05236	0.04439	0.05326
Adjusted R-squared	0.03008	0.03865	0.0315	0.03956

Table 2
Continued

	Volatility		Spread	
	Model 1	Model 2	Model 1	Model 2
Intercept	3.57* (0.014)	3.02* (0.037)	6.59*** (<0.001)	6.43*** (<0.001)
RV	-	2.7*** (<0.001)	-	0.84*** (<0.001)
Sales shock	-1.01 (0.552)	-1.17 (0.488)	0.47 (0.419)	0.42 (0.467)
Sales shock squared	3.64 (0.151)	3.92 (0.120)	0.25 (0.773)	0.33 (0.697)
Size	-0.45*** (<0.001)	-0.39*** (<0.001)	-0.23*** (<0.001)	-0.21*** (<0.001)
Change in size	-0.11 (0.317)	-0.10 (0.392)	-0.05 (0.171)	-0.05 (0.215)
Sales growth	0.01 (0.689)	0.01 (0.712)	0.00 (0.577)	0.00 (0.554)
Concentration ratio	0.68 (0.179)	0.70 (0.164)	0.23 (0.176)	0.24 (0.163)
Resource-growth-mismatch	0.18 (0.351)	0.16 (0.393)	0.04 (0.555)	0.03 (0.606)
Return on assets (ROA)	-11.14*** (<0.001)	-10.67*** (<0.001)	-3.51*** (<0.001)	-3.37*** (<0.001)
Share turnover	0.20 (0.052)	0.15 (0.142)	-0.34*** (<0.001)	-0.36*** (<0.001)
Cash ratio	-1.46** (0.006)	-1.43** (0.007)	-0.34 (0.061)	-0.33 (0.066)
Previous mergers	0.00 (0.958)	-0.01 (0.844)	0.02 (0.44)	0.01 (0.519)
Dormant period	-0.01 (0.339)	-0.01 (0.557)	0.00 (0.524)	0.00 (0.764)
Information asymmetry	-0.82 (0.071)	-0.79 (0.078)	-0.71*** (<0.001)	-0.71*** (<0.001)
Takeover announced within six months	0.69* (0.013)	0.72** (0.009)	-0.09 (0.336)	-0.08 (0.389)
N	1053	1053	1053	1053
R-squared	0.1842	0.195	0.3111	0.3186
Adjusted R-squared	0.1732	0.1833	0.3018	0.3088

Table 3
Mean percentage of total share volume and mean percentage of total cumulative stock-price change by trade size in different venues. Summary results of trades classified as small (100 to 400 shares), medium (500 to 9900 shares), and large (10000 shares and over) are in bold. Sample: 1186 takeover rumor (dropping 51 observations because of no dark pool participation, and 1 observation because the trades did not move the market) from 2006 to 2010. Time period: the rumor date or the next trading day if the rumor date is not a trading day.

Dark Pools					
Trade size (shares)		Percent of total share volume		Percent of total cumulative change	
Small	100	5.23%		11.93%	
	200	2.47%		3.15%	
	300	1.64%		1.31%	
	400	1.31%	**10.65%**	0.73%	**17.12%**
medium	500	1.50%		0.67%	
	600-900	2.59%		0.97%	
	1000-1900	4.13%		0.98%	
	2000-4900	3.68%		0.49%	
	5000-9900	1.58%	**13.48%**	0.15%	**3.25%**
large	10000-19900	0.98%		0.03%	
	20000-49900	1.18%		0.02%	
	50000 and over	2.60%	**4.76%**	0.01%	**0.06%**
	Total	28.90%	**28.90%**	20.43%	**20.43%**

Open markets					
Trade size (shares)		Percent of total share volume		Percent of total cumulative change	
Small	100	25.69%		57.37%	
	200	9.17%		10.03%	
	300	5.20%		4.04%	
	400	3.82%	**43.88%**	1.94%	**73.38%**
medium	500	3.41%		1.69%	
	600-900	5.99%		2.01%	
	1000-1900	6.25%		1.54%	
	2000-4900	5.28%		0.67%	
	5000-9900	2.44%	**23.37%**	0.19%	**6.10%**
large	10000-19900	1.43%		0.05%	
	20000-49900	1.16%		0.02%	
	50000 and over	1.26%	**3.85%**	0.01%	**0.09%**
	Total	71.10%	**71.10%**	79.57%	**79.57%**

Table 4
Mean percentage of total share volume and mean percentage of total cumulative stock-price change by trade size in different quartiles of firm size and different venues. Summary results of trades classified as small (100 to 400 shares) and all trading size are in bold. Sample: Sample: 1100 takeover rumor (dropping 86 observations because of a lack of firm size data) from 2006 to 2010. Time period: the rumor date or the next trading day if the rumor date is not a trading day.

Dark pools

Firm size quartiles	N	Trade size	Percent of total share volume	Percent of total cumulative change
0%-25% Q1	275	Small	10.39%	17.46%
		Medium	13.57%	3.50%
		Large	4.73%	0.06%
25%-50% Q2	275	Small	10.51%	15.29%
		Medium	14.21%	3.50%
		Large	4.73%	0.07%
50%-75% Q3	275	Small	10.67%	16.57%
		Medium	12.64%	2.95%
		Large	5.09%	0.04%
75%-100% Q4	275	Small	11.04%	19.11%
		Medium	13.51%	3.07%
		Large	4.51%	0.06%

Open markets

Firm size quartiles	N	Trade size	Percent of total share volume	Percent of total cumulative change
0%-25% Q1	275	Small	44.09%	71.46%
		Medium	23.02%	7.43%
		Large	4.21%	0.10%
25%-50% Q2	275	Small	43.58%	74.04%
		Medium	23.50%	7.03%
		Large	3.48%	0.07%
50%-75% Q3	275	Small	45.39%	74.37%
		Medium	22.72%	6.02%
		Large	3.48%	0.05%
75%-100% Q4	275	Small	42.50%	73.68%
		Medium	24.22%	3.94%
		Large	4.22%	0.13%

Table 5

Mean percentage of total share volume and mean percentage of total cumulative stock-price change by trade size in different quartile of ROA and different venues. Summary results of trades classified as small (100 to 400 shares) and all trading size are in bold. Sample: 1100 takeover rumor (dropped 86 observations because a lack of ROA data) from 2006 to 2010. Time period: the rumor date or the next trading day if the rumor date is not a trading day.

Dark pools				
ROA quartiles	N	Trade size	Percent of total share volume	Percent of total cumulative change
0%-25% Q1	275	Small	10.77%	18.58%
		Medium	13.19%	2.35%
		Large	4.50%	0.07%
25%-50% Q2	275	Small	10.43%	15.61%
		Medium	12.76%	3.01%
		Large	4.88%	0.05%
50%-75% Q3	275	Small	10.42%	17.37%
		Medium	14.84%	3.79%
		Large	4.46%	0.07%
75%-100% Q4	275	Small	11.01%	16.95%
		Medium	13.12%	3.85%
		Large	5.21%	0.04%

Open markets				
ROA quartiles	N	Trade size	Percent of total share volume	Percent of total cumulative change
0%-25% Q1	275	Small	44.36%	72.34%
		Medium	23.05%	6.59%
		Large	4.13%	0.08%
25%-50% Q2	275	Small	44.29%	73.96%
		Medium	24.03%	7.31%
		Large	3.60%	0.07%
50%-75% Q3	275	Small	42.32%	71.25%
		Medium	23.84%	7.41%
		Large	4.13%	0.11%
75%-100% Q4	275	Small	44.59%	76.00%
		Medium	22.53%	3.07%
		Large	3.54%	0.08%

Table 6

Mean percentage of total share volume and mean percentage of total cumulative stock-price change by trade size in different rumor accuracy and different venues. Summary results of trades classified as small (100 to 400 shares) and all trading size are in bold. Sample: 1186 takeover rumor (dropping 51 observations because of no dark pool participation, and 1 observation because the trades did not move the market) from 2006 to 2010. Time period: the rumor date or the next trading day if the rumor date is not a trading day.

Dark pools				
Rumor Accuracy	N	Trade size	Percent of total share volume	Percent of total cumulative change
Accurate at 6 months	168	Small	10.11%	17.27%
		Medium	12.43%	3.56%
		Large	5.69%	0.04%
Inaccurate at 6 months	1018	Small	10.74%	17.09%
		Medium	13.66%	3.20%
		Large	4.61%	0.06%
Accurate at 1 year	233	Small	10.21%	17.26%
		Medium	13.11%	3.80%
		Large	5.30%	0.05%
Inaccurate at 1 year	953	Small	10.76%	17.09%
		Medium	13.58%	3.12%
		Large	4.63%	0.06%

Open markets				
Rumor Accuracy	N	Trade size	Percent of total share volume	Percent of total cumulative change
Accurate at 6 months	168	Small	40.30%	71.11%
		Medium	26.31%	7.90%
		Large	5.17%	0.11%
Inaccurate at 6 months	1018	Small	44.47%	73.76%
		Medium	22.88%	5.80%
		Large	3.63%	0.08%
Accurate at 1 year	233	Small	40.34%	71.06%
		Medium	25.99%	7.74%
		Large	5.05%	0.09%
Inaccurate at 1 year	953	Small	44.75%	73.95%
		Medium	22.73%	5.70%
		Large	3.56%	0.09%

Table 7

Mean percentage of total share volume and mean percentage of total cumulative stock-price change by trade size in different quantile of the relative dark pool trading volume and different venues. Summary results of trades classified as small (100 to 400 shares) and all trading size are in bold. Sample: 1186 takeover rumor (dropping 51 observations because of no dark pool participation, and 1 observation because the trades did not move the market) from 2006 to 2010. Time period: the rumor date or the next trading day if the rumor date is not a trading day.

Dark pools				
Volume quantiles	N	Trade size	Percent of total share volume	Percent of total cumulative change
0%-25% Q1	296	Small	6.23%	8.99%
		Medium	5.23%	1.24%
		Large	1.65%	0.02%
25%-50% Q2	297	Small	10.99 %	15.03%
		Medium	9.47%	2.14%
		Large	3.93%	0.01%
50%-75% Q3	297	Small	12.86%	19.96%
		Medium	14.16%	3.57%
		Large	4.93%	0.09%
75%-100% Q4	296	Small	12.54%	24.50%
		Medium	25.06%	6.06%
		Large	8.53%	0.11%

Open markets				
Volume quantiles	N	Trade size	Percent of total share volume	Percent of total cumulative change
0%-25% Q1	296	Small	51.81%	80.34%
		Medium	29.73%	9.29%
		Large	5.35%	0.12%
25%-50% Q2	297	Small	49.39%	80.05%
		Medium	22.48%	2.69%
		Large	3.73%	0.08%
50%-75% Q3	297	Small	43.57%	70.36%
		Medium	21.07%	5.96%
		Large	3.42%	0.05%
75%-100% Q4	296	Small	30.78%	62.79%
		Medium	20.18%	6.43%
		Large	2.90%	0.10%

Table 8
Mean percentage of total share volume and mean percentage of total cumulative stock-price change by trade size in different year. Summary results of trades classified as small (100 to 400 shares) and all trading size are in bold. Sample: 1186 takeover rumor (dropping 51 observations because of no dark pool participation, and 1 observation because the trades did not move the market) from 2006 to 2010. Time period: the rumor date or the next trading day if the rumor date is not a trading day.

Dark pools

Year	N	Trade size	Percent of total share volume	Percent of total cumulative change
2006	138	Small	5.57%	14.97%
		All size	16.88%	18.16%
2007	178	Small	6.56%	10.98%
		All size	21.33%	13.42%
2008	178	Small	11.16%	19.44%
		All size	31.06%	22.74%
2009	347	Small	12.43%	17.76%
		All size	33.50%	22.01%
2010	345	Small	12.74%	19.31%
		All size	31.87%	22.18%

Open markets

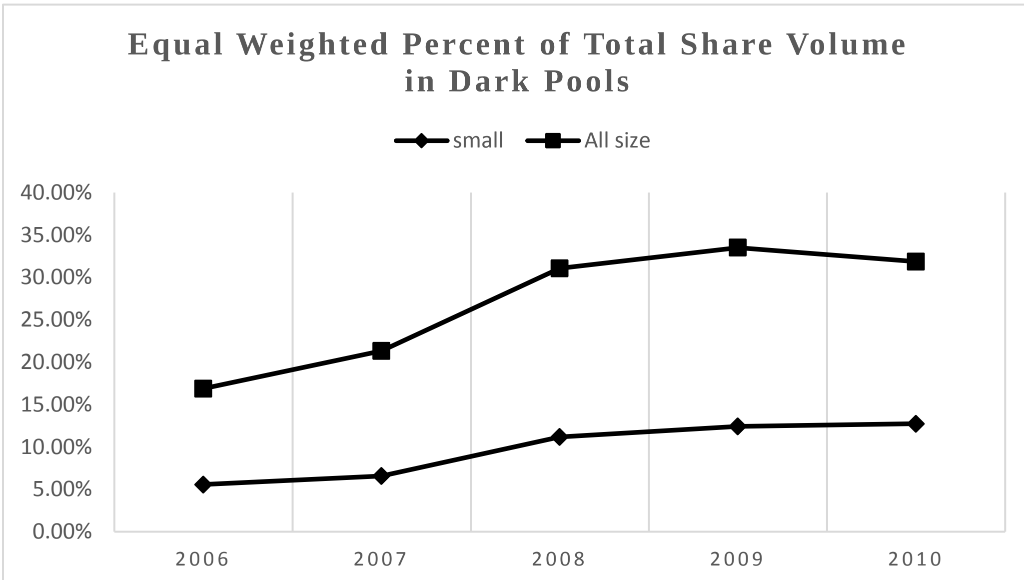
Year	N	Trade size	Percent of total share volume	Percent of total cumulative change
2006	138	Small	34.26%	66.71%
		All size	83.12%	81.84%
2007	178	Small	43.87%	77.41%
		All size	78.67%	86.58%
2008	178	Small	42.18%	75.33%
		All size	68.94%	77.26%
2009	347	Small	45.89%	73.02%
		All size	66.50%	77.99%
2010	345	Small	46.60%	73.34%
		All size	68.13%	77.82%

Table 9

Mean share volume in dark pools, mean share volume in open markets and percent of mean share volume in dark pools by trade size in different year. Summary results of trades classified as small (100 to 400 shares) and all trading size are in bold. Sample: 1186 takeover rumor (dropping 51 observations because of no dark pool participation, and 1 observation because the trades did not move the market) from 2006 to 2010. Time period: the rumor date or the next trading day if the rumor date is not a trading day.

Year	N	Trade size	Mean share volume in dark pools	Mean share volume in open markets	Percent of mean share volume in dark pools
2006	138	Small	295552.68	1265726.40	18.93%
		All size	1120261.33	4695964.70	19.26%
2007	178	Small	345396.10	1919091.40	15.25%
		All size	1418730.11	4506680.30	23.94%
2008	178	Small	594337.02	2100061.32	22.06%
		All size	1763195.66	3871007.95	31.29%
2009	347	Small	661247.53	2456435.57	21.21%
		All size	2476971.09	4410592.06	35.96%
2010	345	Small	727944.06	2636275.92	21.64%
		All size	2342883.37	4511409.33	34.18%

Figure 1
The trend in equal weighted average percentage of total share volume and percentage of total cumulative stock price change in dark pool from 2006 to 2010.



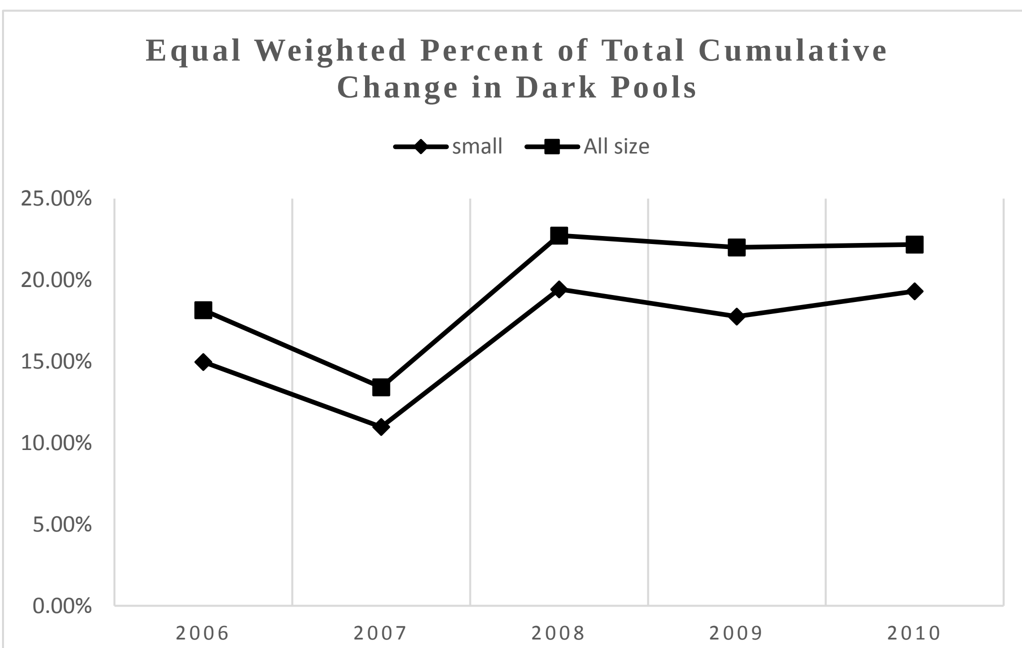


Figure 2
The trend in the value weighted average percentage of share volume in dark pools from 2006 to 2010.